

FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

SAE Light Controller – Automatic vehicle location using mobile devices

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Abstract

Automatic Vehicle Location (AVL) is a means for automatically determining and transmitting the geographic location of a vehicle. Nowadays, Global Positioning System (GPS) is the most stable implementation of satellite-based location systems, therefore being the most common way of determining a vehicle's location in AVL systems.

Currently, in major cities, public transports have a very accurate, but very expensive, AVL system installed in each vehicle, making it unaffordable for smaller public transport operators to acquire this kind of equipment. On the other hand, GPS-enabled mobile devices are becoming increasingly more ubiquitous while their processing power and batteries are improving.

This work intends to propose the use of mobile devices as an alternative to traditional AVL systems for public transports. These devices represent a cheaper option for public transport operators which would provide smaller companies with a more cost-efficient method of keeping track of the positions of their automotive vehicles. Furthermore, this work also intends to propose an algorithm for the identification, in real-time, of deviations from the planned schedule.

The first step consists in analysing algorithms for geolocation in order to identify the most accurate one, given the public transport's predefined route. The second step is the implementation of an AVL's interface and functionality for mobile devices for the calculation of the Travel Time Prediction (TTP). The third step is the development of an algorithm, using Kalman filters, that predicts schedule deviations in real-time and informs bus drivers and passengers of them. Finally, the last step is to compare the obtained results of this system with the one already in use on the market, regarding the cost-efficiency relation between them, in order to determine the viability of the developed system for use in public transportation.

Resumo

Localização Automática de Veículos (AVL) é um meio para determinar e transmitir a localização geográfica de um veículo automaticamente. Hoje em dia, o Sistema de Posicionamento Global (GPS) é a implementação mais estável de sistemas de localização baseados em satélites, sendo, conseqüentemente, a forma mais comum de determinação de localização de um veículo em sistemas AVL.

Atualmente, nas grandes cidades, os transportes públicos têm um sistema AVL muito preciso, mas muito caro, instalado em cada veículo, tornando-o inviável para os pequenos operadores de transportes públicos para adquirir este tipo de equipamento. Por outro lado, os dispositivos móveis com GPS estão a tornar-se cada vez mais presentes, enquanto o seu poder de processamento e as baterias estão a melhorar.

Este trabalho pretende propor o uso de dispositivos móveis como uma alternativa aos sistemas tradicionais AVL para transportes públicos. Estes dispositivos representam uma opção mais barata para os operadores de transportes públicos, o que proporciona às pequenas empresas um método mais eficiente, em termos de custo, de manter o controlo das posições dos seus veículos. Além disso, este trabalho também pretende propor um algoritmo para a identificação, em tempo real, de desvios do cronograma planeado.

O primeiro passo consiste em analisar algoritmos para geolocalização, a fim de identificar o mais preciso, dado um percurso predefinido do transporte público. O segundo passo é a implementação de uma interface e funcionalidades de um AVL orientado a dispositivos móveis para o cálculo da Previsão do Tempo de Viagem (TTP). O terceiro passo é o desenvolvimento de um algoritmo, usando filtros de Kalman, que prevê desvios no cumprimento do horário em tempo real e informa os motoristas de autocarros e passageiros destes desvios. Finalmente, a última etapa é comparar os resultados obtidos no presente sistema com o já em uso no mercado, no que respeita a relação custo-eficiência entre eles, a fim de determinar a viabilidade do sistema desenvolvido para o uso em transportes públicos.

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Cristiano Seabra

*“I see now that the circumstances of one’s birth are irrelevant.
It is what you do with the gift of life that determines who you are.”*

Takeshi Shudo

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Abbreviations

APC	Automatic Passenger Counting
AVL	Automatic Vehicle Location
CDMA	Code Division Multiple Access
FEUP	Faculdade de Engenharia da Universidade do Porto
GPS	Global Positioning System
GSM	Global System for Mobile Communications
GSMPS	Global System for Mobile Communications Positioning System
ITS	Intelligent Transport Systems
RFID	Radio Frequency Identification
STCP	Sociedade de Transportes Coletivos do Porto
TT	Travel Time
TTP	Travel Time Prediction
UDP	User Datagram Protocol
WPS	Wi-Fi Positioning System

Chapter 1

Introduction

1.1 Context

Intelligent Transport Systems (ITS) help drivers in carrying out their task. These bring advantages, depending on their configuration, as the level of safety, comfort and ease of driving, always ensuring that the final decision remains with the driver.

Global Positioning System (GPS) is a space-based navigation system, based on satellites, that is widely used nowadays. These systems have a long history of use by maritime and aeronautical transport, however recent GPS applications on land had several improvements, such system control capabilities [MBP⁺04].

Automatic Vehicle Location (AVL) is a means for automatically determining and transmitting the geographic location of a vehicle. The use of GPS-based AVL systems brought to the transit industry and public transport companies an efficient way in performance and associated costs, largely due to the fact that GPS systems are becoming cheaper and compact, in order to control operations of their vehicles [PRM⁺10]. These ITS provide users with reliable and up-to-date information such as time and location, i.e., how long the vehicle will take to reach the desired destination, or the location where the vehicle is at any given time. This capability is important because it attracts more users to attend these public transport and help to better plan their transit and multimodal trip itineraries and allows them to make better decisions before and during the use of public transports.

1.2 Motivation and Goals

The cost of AVL devices presents a significant investment, which mainly affects the development of small and medium-sized public transportation companies.

Therefore, this work will focus on the development of an application capable of performing the functionality of an AVL system based on GPS to calculate Travel Time Prediction (TTP), capable of running on an Android mobile device, since such a measure would provide a low-cost alternative to existing AVL devices. At the same time, these features will be analysed for the

cost-benefit relation, as it is important to maintain a level of reliability and accuracy, considered adequate, to the operational requirements of the public transport networks in the current context. It will also be analysed the fulfilment of the time schedule in order to inform the driver and the users of the vehicle's relative position within the preset timetable.

1.3 Structure of this document

Besides this introductory chapter, this document contains 3 more chapters. In chapter 2 we review the existing literature on the topic and present some related works. After that, in chapter 3, we present the idea and potential of SAE Light Controller, as well the methodology planned and major challenges. In chapter 4 we present how we implemented our solution, as well as the chosen design and the necessary requirements for its operation. In chapter 5 we present and explain the obtained results and discuss these to verify the successfulness of our solution in the context of our problem. Lastly, in chapter 6 we conclude this dissertation about AVL systems and introduce some future work to possibly obtain more accurate results in the calculation of TTP and some features for the deployment of SAE Light Controller on the market.

Chapter 2

Literature Review

2.1 Introduction

This chapter aims to map out some work previously performed in the area of Intelligent Transportation Systems (ITS), the use of Automatic Vehicle Location (AVL) systems and use of algorithms for increased data accuracy.

At the time of writing, there are several works done by researchers in these areas and that allows us to have a solid basis for the preparation of this work. This solid foundation provides us the best way to solve the problem and therefore drawing important conclusions that are present in the last section of this chapter.

2.2 Intelligent transportation systems (ITS)

Transportation flows are more and more monitored and controlled with systems of diverse technologies. However, it proves difficult to visualize the data generated by travelling. Therefore, it may be difficult to visualize how others might be interpreting, sharing and responding to these data, and how individual or automated reactions to these data will modify mobilities or experiences [Mon07]. For this reason, ITS have been deployed around the world, mostly in major cities.

Intelligent Transportation Systems (ITS) are advanced applications comprised by a heterogeneous network of technologies for highways and roads. These applications aim to provide innovative services relating to different modes of transport and traffic management, without intelligence as such. Because of this, ITS make safer, more coordinated and "smarter" use of transport networks.

The main advantage of using ITS with transport networks is the translation of transportation flows into data that can be used, if possible in real-time, through predictive modelling [Mon07]. Also, ITS allows to obtain very useful data for purposes of efficiency, security and commercial marketing. Some examples are:

- In public transportation, GPS can be used to track the exact location of trains and buses;

Literature Review

- Smart cards embedded with radio frequency identification (RFID) allow for automated electronic payment for the use of highways and bridges;
- License-plated recognition systems are deployed to minimize traffic congestion and assessing fines;
- Systems for in-car utilisation, such as black boxes, GPS units, or vehicle-to-vehicle communication technologies, allow an increased inspection by insurance companies, marketers, rental car agencies, law enforcement and others.

Although GPS localization and Automatic Passenger Counting (APC) are the most popular information to be obtained by automated data collection systems from on-board sensors, Moreira-Matias *et al* [MMMMSG15] presents other potentially valuable data items in his work:

- Stop and start moment: by recording when the vehicle starts and stops, information regarding dwell time (the amount of time the vehicle is in a given state) and holding (the amount of time spent at a stop) can be obtained.
- Event codes: these range from automated mechanical alarms or flags to manually entered alarms.
- Control messages: through the establishment of a communication channel from the control centre to the operator, messages reporting the corrective actions necessary to restore service normality after it has deviated can be sent.
- Farebox transactions: by recording information about ticket validation (especially its type), statistics about the passengers served by a given route can be calculated. This is helpful in many planning and control tasks, including maintenance scheduling, route designing and timetabling, corrective control actions and route designing. Due to this, these types of data items are already deployed in many AVL systems worldwide.

2.2.1 Global Positioning System (GPS)

Global Positioning System (GPS) is a satellite positioning system, composed of a network of 27 or more satellites that orbit the Earth, that provides information about position, accurate timing and velocity [TYK05], regardless of atmospheric conditions, time of day or location, as long as the receiver finds at least three GPS satellites in his/her field of view. By making use of four or more satellites, the accuracy of the measurements can be increased.

The positioning data provided by GPS is obtained through the method known by triangulation. This process allows to find a particular place on Earth, by knowing the distances between the GPS receiver and the GPS satellites, and then by calculating the distance (by receiving microwaves from the satellites) between the receiver and at least three satellites. These distances are now the

radii on three separate spheres and the location that is to be calculated is derived from the point at which the three spheres intersect [TYK05], as shown in Figure 2.1¹.

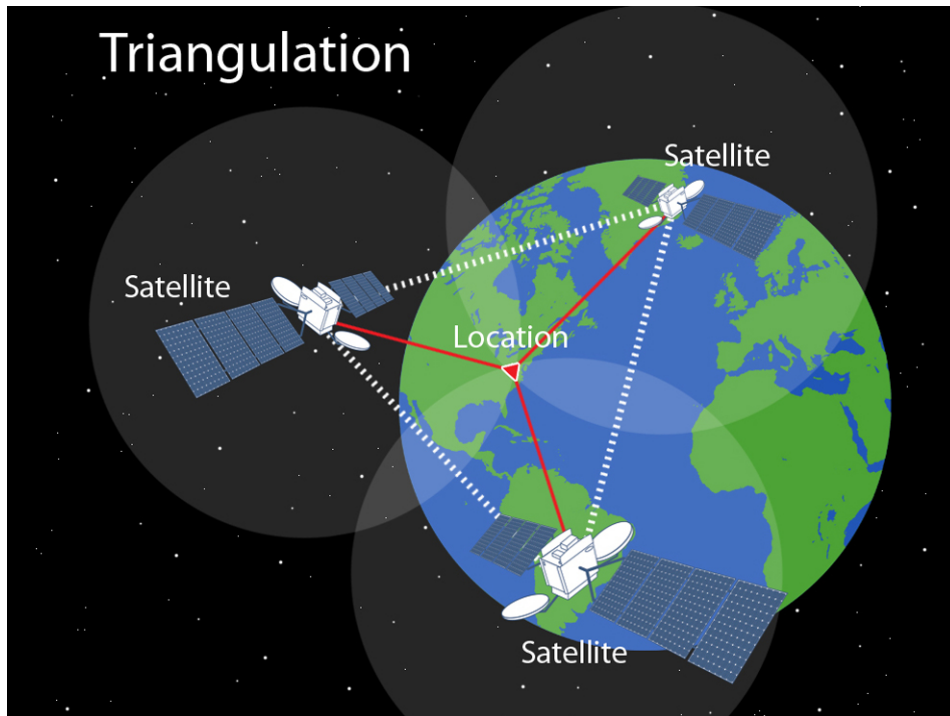


Figure 2.1: GPS triangulation process

Nowadays, due to its reliability and availability, GPS is considered the most efficient vehicle locating method, and is the most widely implemented one [PRM⁺10]. Even in more remote areas, the advances made regarding the sensitivity of GPS receivers allows them to work reliably. This contrasts to other locating methods, such as Radio Frequency Identification (RFID), which pose significant set-up costs related to the deployment and maintenance of the complete network of sensors and power supplies that providing a monitoring service based on them would require.

The way location tracking works is briefly explained in Figure 2.2². The vehicle, equipped with a GPS receiver, obtains its position from GPS satellites. This location data is sent to a cellular base station, through a GSM (Global System for Mobile Communications) or CDMA (Code Division Multiple Access) modem, and then sent to a tracking system. This tracking system finally sends the data to a client server.

The continuous location sensing using GPS systems on mobile devices comes with a great energy cost. For example, GPS provides location accuracy to within 10m, but constantly checking for position updates, as in real-time applications, can deplete the battery in approximately 12 hours [OPM12].

¹<http://www.howtechnologywork.com/wp-content/uploads/2014/12/GPS-Triangulation.jpg>

²<http://www.buzzle.com/images/electronics/how-location-tracking-works.jpg>

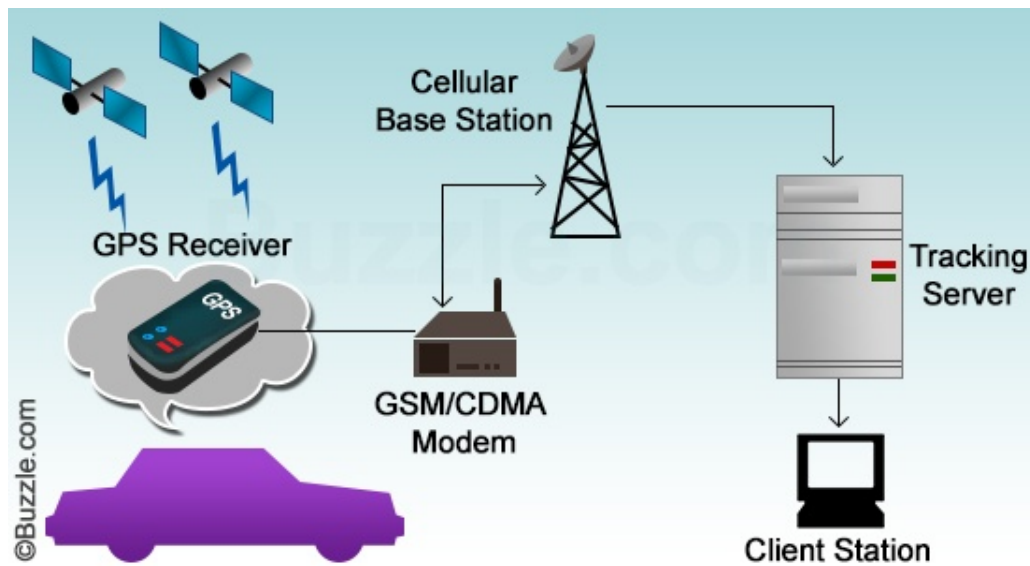


Figure 2.2: Brief explanation of location tracking

However, smartphones are equipped with real-time sensing and user activity recognition by using, for example, very common sensors such as accelerometers, and other alternatives for location sensing technologies such as Wi-Fi Positioning System (WPS) and Global System for Mobile Communications Positioning System (GSMPS). Nevertheless, the biggest problem of using WPS and GSMPS for improving the energy-efficiency of GPS is the increased average localization error. The location accuracy, in urban areas, for WPS and GSMPS are approximately 20-30m and 70-200m respectively [OPM12], which may prove to be very difficult to use in real-time applications that need to have accurate results to achieve their goals.

2.2.2 Automatic Vehicle Location (AVL)

Automatic Vehicle Location (AVL) is a means for automatically obtaining and transmitting the geolocation of a vehicle to an appropriate tracking system in order to provide an overview of its travel pattern.

Automatic vehicle locating is commonly used for managing fleets of vehicles, be they service vehicles, emergency vehicles, precious construction equipment, or public transport vehicles (buses and trains). It is also used to track mobile assets, such as non wheeled construction equipment, non motorized trailers, and mobile power generators.

With the increase in traffic congestion and, therefore, passenger demands, many public transport operators seek to improve their operations by investing in this technology, which holds substantial promise for improving service planning, timetable scheduling and performance analysis practices [FHMS03].

Today's bus AVL systems include the core location tracking capabilities and other additional functionalities, with some obtained through other sensors and devices in the bus, such as [Par08]:

- Text messaging data communications between operators and dispatch;



Figure 2.3: Display in a London's bus

- Manager of headsign and farebox;
- Onboard next stop announcements that are automatically triggered as the vehicle approaches the stop, by voice and/or displays (such as Figure 2.3³);
- Onboard automatic passenger counting (APC) equipment to record the number of passengers boarding;
- Show some vehicle's monitor status messages;
- Use schedule adherence and/or location data to develop real-time predictions for bus arrival times at stops and inform passengers through the use of several methods, such as dynamic message signs (Figure 2.4⁴);
- Covert alarm to send an emergency message to dispatch, sometimes with a covert microphone for audio monitoring from dispatch.

The use of these AVL system capabilities create huge benefits for public transportation. Namely for fixed-route systems, these benefits include:

- Improved situational awareness and additional voice communications management capabilities for dispatchers, that extends the size of fleet that can be handled by each dispatcher;

³https://upload.wikimedia.org/wikipedia/commons/7/76/London_iBus_display.JPG

⁴<http://www.psta.net/images/Dynamic-Message-Sign.jpg>



Figure 2.4: Dynamic message sign at a bus stop

- Maximize on-time performance and reliability through the transmission of schedule adherence feedback;
- Increased help efficiency by dispatchers and supervisors to react and be proactive in addressing operational issues, through the use of text messaging, covert alarm monitoring, etc;
- A single point for the operator to login and manage headsigns and farebox data, maximizing schedule adherence;
- Reduced operator workload by automatically announce next stops, providing consistent information for passengers;
- Real-time next bus predictions to clients, which can help ridership, reducing customer anxiety, by enhancing reliability;
- Reliable data collection and incident reporting, providing more effective and detailed analysis.

One of the data types provided by AVL systems is location. Most often, the location is determined using GPS and the Global System for Mobile Communications (GSM) is the most common channel to be used as the mechanism for transmitting the information. This occurs mainly because of the low data rate needed by AVL systems and the low cost and near-ubiquitous nature of this public network [PRM⁺10].

AVL output consists of an array of points in time and two dimensional space, representing a set of coordinates at a given timestamp. This form of location data is well suited for vehicle location visualization on a map or for determining whether a certain vehicle is following its assigned route.

Furthermore, the coordinates in this array can be transformed into a single value representing the distance between the current position and the next stop in the vehicle's route. This transformation leads to a shift from a three dimensional problem (latitude, longitude and time) to a two dimensional problem (time and one spatial dimension), which is easier to compute.

2.3 Travel Time Prediction (TTP)

Moreira-Matias *et al* define Travel Time Predictions (TTP) as one of the most common problems in transportation [MMMMdSG15].

As stated by Lin *et al*, being able to receive, from traveller information systems, information on bus arrival time at bus stops could reduce the anxiety of passengers waiting for the bus [LZ99]. Message signs or applications displaying this information are being used right now in major cities around the globe, helping to improve the reliability and effectiveness of traveller information services and commuters' satisfaction with the service offered. AVL, frequently presented as a source of a vehicle's position information, produces data suitable for obtaining arrival time predictions [PRM⁺10].

TTP can be used in several other contexts besides fleet management, such as logistics, individual navigation or mass transit, planning, monitoring, and control. Although some approaches seem quite simple, there are various methodologies that could be applied to TTP problems from different research areas. Moreira-Matias divides these approaches into four different categories [MMMMdSG15]:

- **Machine Learning and Regression Methods:** these methods make use of a mathematical function based on a set of independent variables to infer the arrival time (the dependent variable). Regression models have been the state of the art on this kind of approach for the last two decades. These methods are mainly used to estimate and plan the timetable schedule of a public transport and not used for real-time analysis.
- **State-Based and Time Series Models:** these methods only take into account the most recent data samples, and thus do not depend as much on the amount of data, nor do they require a large training period, as they mainly represent online learning algorithms. This ability to learn and update in real-time makes them able to react well to unexpected events that may affect the expected traffic flow, such as heavy rains, traffic jams, sports matches, and car accidents. While the time series models assume that the Travel Time (TT) is a linear/nonlinear combination of its historical values, the state-based approaches usually assume that the future state of the dependent variables only relies on the most recent states. The most popular state-based model is the Kalman filter. The main advantage of this model when compared

with Markovian approaches is its ability to filter noise in the data, which is extremely relevant in online learning tasks for short-term prediction problems.

- **Flow Conservation Equations and Traffic Dynamics Models:** these methods focus on formulating the Travel Time (TT) between two points as a sum of the TT between smaller stretches of the route being analysed (i.e., roads). This is done by applying relations between traffic variables obtained from the traffic flow theory.
- **On Evaluating TTP Models:** these methods consist of simple averages and other types of time-varying Poisson processes whose average Travel Time (TT) is defined by its historical values depending on the day type and/or on the period of the day. Due to the simplicity of these models, they are unable to represent complex relationships between the TT and other variables present in urban public transport networks, and are therefore usually considered to be a poor approach to TTP.

As stated in Moreira-Matias [MMMMdSG15], AVL systems and their large-scale introduction in public transportation around the world created new opportunities to operational controllers and made it possible to create highly sophisticated control centres to monitor all the vehicles in real-time. However, this requires a large amount of human resources. By exploring the historical data from AVL systems, researchers started to build automatic control strategies, which can maintain the buses on schedule, while reducing the number of human resources needed in the process. Therefore, some corrective actions have been employed as real-time control strategies:

- **Bus holding:** It consists of forcing the driver to increase, or decrease, the dwell time on a bus stop along the route;
- **Speed modification:** This strategy consists of forcing the driver to reduce the maximum cruise speed on its course, comparative to what's usual on that specific route;
- **Stop-skipping:** When it is required to make a path change to reduce the original length of the route, the driver must skip some route stops;
- **Short-turning:** This technique forces the driver to skip the remaining bus stops, usually at its terminus, in order to fill a large gap in another route, sometimes forcing the passengers to transfer to another transportation.

Bus holding strategies are the most classic way of keeping the bus on-schedule. However, this strategies, as well as speed modification, are made by increasing the TT of the passengers in the vehicle. Moreover, stop-skipping and short-turning strategies corrects the time schedule by keeping the passengers waiting on the stops that were skipped [MMMMdSG15].

2.3.1 Kalman filter

As mentioned earlier, Kalman filters have emerged over time as a very reliable implementation solution and are widely used by many researchers for the task of calculating the TTP for state-based models, namely those intended for real-time use [MMMMdSG15].

The Kalman filter is a linear recursive predictive update algorithm invented in 1960 by Rudolf Emil Kalman, that is used to estimate the parameters of a process model [Kal60].

From an engineering standpoint, it is normal to try to create linear mathematical models of real systems. So, when these implicate non-linearity, it is logical to attempt to linearise the system to an operating point. A linear system is easier to handle with existing mathematical tools and the theory which supports these systems is much more complete and practical than the one supporting nonlinear ones. Nonetheless, some systems are impossible to linearise, though there are variants of the Kalman filter that specifically deal with nonlinear systems [May82].

As Predic *et al* stated, the Kalman filter's ability to combine the effects of noise on both the process and the measurements and the computationally manageable nature of its algorithms made it very popular, namely in the areas of autonomous and assisted navigation [PRM⁺10].

It is important to note that as this filter was developed for treating linear systems, it can only be an optimal state estimator if the system is linear and the noise of the process and the measures are white and Gaussian [May82].

Past data used as input to the Kalman filter is collected from the previous bus runs, even on the same day, and the accuracy of this input can increase by having past days' data [PRM⁺10].

For the GPS' implementations on mobile devices, the use of Kalman filters appears to vary depending on the hardware used and the system's implementation. There are, however, ways to identify if a particular device implements these filters by analysing the system's log output ⁵.

2.4 Relevant Projects and Research

Systems dealing with prediction problems in public transportation exist either as scientific projects or as commercial solutions that have been implemented in many cities [PRM⁺10].

MYBUS (2001) is the result of a scientific project developed for ITS at the University of Washington. A Kalman filter is used to stream location and velocity data for each bus and then mapped to match the geometry of the route on which the bus is operating. This geometry is divided into several smaller segments, in order to estimate the time the bus will take to arrive at the station. This way, it is practicable to assume that the vehicle will be travelling at a constant speed on each segment. In the end, the final estimated time is the sum of the calculated times per segment. However, speed can change very easily because of the city's traffic conditions unpredictability. Therefore, predictions based solely on speed can be very unstable [PRM⁺10]. This is why Predic *et al* state the usefulness of AVL systems based on GPS for obtaining the vehicle's location and

⁵<http://gis.stackexchange.com/questions/87182/what-class-types-of-smartphone-chipsets-support-gps-a-gps-qlonass-and-have-ext>

then estimate the time the bus will take to arrive the station, in a more dynamic way, using Kalman filters.

Also, it is stated that Shalaby and Farhan (2004) compared their proposed method to other previously developed models and the use of Kalman filters exhibited better predictive performance in the simulated environments, with dynamic changes due to different characteristics of bus operation. In addition to its performance, since the model separates the bus dwell time prediction from the bus running time prediction, it has the advantage of capturing the effects of control strategies [PRM⁺10]. This research deals with unpredictabilities in bus operations such as traffic accidents and varying number of passengers boarding and leaving the bus at certain stops.

2.5 Conclusions

The literature proves the huge benefits of using AVL systems in public transportation. Their accuracy and effectiveness improves the reliability and user experience, decreasing passenger's anxiety and increasing ridership. It's a great tool for drivers, because it provides them useful information, but even more for the companies that use this data for planning schedule updates, new routes or service plans adapted to new circumstances.

Besides all the ITS functions implemented in public transportation, AVL's basic function of automatically locating a vehicle's position, through the use of GPS, is extremely accurate due to the fact that the GPS receiver used in AVL systems has Kalman filters implemented on. Therefore, the use of Kalman filters in vehicle location is really important to reduce noise and maximize accuracy in data gathering for the TTP and vehicle positioning on map. This focus on accuracy and all the other functions that an AVL gathers, is what makes this kind of device excel and become such a valuable tool for operators to acquire.

It is also stated in the literature that it is possible, through the use of state-based models and Kalman filters, that the development of real-time applications of vehicle tracking and TTP calculation for time scheduling is possible. It is also stated that mobile devices do not pose a major challenge to implement these applications on.

Chapter 3

SAE Light Controller

3.1 Introduction

Knowing about the utilisation of AVL systems in public transportation, as mentioned in the previous chapter, we propose the development of SAE Light Controller.

SAE Light Controller is an application for mobile devices, namely those with the Android operating system, in order to be a light and capable application to perform the functions of an AVL system currently used in public transportation, in order to make it possible to acquire a mobile device with the application, rather than purchasing expensive AVL systems, for the calculation of the TTP.

This solution will automatically detect the vehicle's location, velocity and travelled distance, in real-time, and, by knowing the elapsed time, apply a Kalman filter to get the estimated arrival time. This way, the drivers, using SAE Light Controller, will be able to control the time schedule, just from looking at the mobile device, and know if the bus is ahead or behind schedule. This process is automatic and the drivers only have to input the route's number, direction and start time and, after a button click, see their position on the map and the estimated arrival time.

The ultimate goal of this dissertation is to compare the performance of SAE Light Controller with AVL systems currently used nowadays, to check if the cost reduction is sufficiently capable to compete with these AVL systems.

3.2 Architecture

The implementation's structure of the application is illustrated in [Figure 3.1](#).

SAE Light Controller is composed of two different activities:

- Main activity: a simple screen, with only three input requirements for the driver to identify the desired line trip. This data is sent to the server that will query the database, where the route's details are stored, and get the necessary data needed to apply the Kalman filters. After this, the data is consequently sent to the Maps Activity.

SAE Light Controller



Figure 3.1: Planned architecture for SAE Light Controller

- **Maps activity:** a Google Maps API v2 map display that pinpoints the bus' location, through the use of GPS, and displays the estimated time of arrival to the driver, so he/she is able to know if the bus is behind or ahead schedule. In this activity's background, the filtered data is sent to the server to store in the database, so that, in the future, drivers using the application will be able to know other driver's locations and customers will be able to know how if the buses are behind or ahead schedule.

3.3 Data collection methodology

The data collection process consists of travelling by bus, with both SAE Light Controller and the server running, and store all the data needed for:

- Identifying the bus trip to relate the filtered data to a specific trip using the driver's route, direction and starting time inputs;
- Tracking the bus trip, registering its position with its latitude, longitude and timestamp;
- Analysing the efficiency of using Kalman filters to measure the TTP by storing the variables used in the calculations such as velocity and accuracy of the measurements in a specific position, trip's total distance, current travelled distance and others further described.

These measurements are collected, calculated and stored in a 5 seconds' timespan.

The Sociedade de Transportes Coletivos do Porto (STCP), a public transportation company at Porto, Portugal, provided some data regarding some of its routes. The routes are:

- 301: A single direction circular bus trip around the city. As the provided route with the biggest total distance, this one was tested 2 times. The scheduled start and end times of the first bus trip were 10:00 a.m. and 11:14 a.m. respectively. The second bus trip started at 5:05 p.m and ended at 6:23 p.m..
- 401: A bidirectional bus trip between Bolhão and S. Roque. The direction "Volta", with start in S. Roque, had to be discarded due to some road maintenance that diverted from the original bus route, therefore not allowing the use of the data provided for that route. The direction with starting point at Bolhão was tested 1 time.

Due to lack of time, only a total of 3 tests were made.

3.4 Major challenges and risks

The development and testing phases of SAE Light Controller may present some challenges and risks and some of them could be already identified.

The identified challenges are:

- The main challenge of this dissertation is to provide a better cost-efficient alternative to AVL systems. Therefore, it's important to keep a competitive level of location, time and velocity accuracy, compared to an existing AVL, to calculate a good estimate of arrival time and make it viable to decrease the cost of the equipment.
- The battery level of the mobile device must not deplete while the public transport is working actively. Because of the high GPS usage, the battery depletes fast, therefore the use of a lighter charger is mandatory and enough to solve this problem.
- The type of data and how it is structured on the companies' databases may prove to be a challenge for the application to process. This poses a major challenge because if, for example, the company has more detailed information about distances between stops the algorithm can be highly improved.
- The testing phase needs some real-time field work, making the analyses much easier if some cooperation is established with the companies, making it possible to execute more bus' runs and collect more data.

The identified risks are as follows:

- A continuous connection with GPS and Wi-Fi must be available because it's crucial for transmitting and receiving data and therefore obtain good results.
- The databases with public transportation lines and timetables may differ between companies, making the current implementation incapable of working thanks to the specific queries to the database.

- The driver of the public transport should make the right inputs. Otherwise, it may lead the application to work with wrong lines and/or time schedules because it doesn't identify the right route, it chooses another route or it simply isn't capable to connect to server.

3.5 Conclusions

SAE Light Controller focuses on the consequences of using an AVL in the detection of a vehicle's location, analysis of compliance with the timetable and the processing and visualisation of these data, to improve the experience of drivers and users of public transports, trying to maintain a competitive data accuracy in calculating the travel time prediction.

In this chapter we detailed some features of SAE Light Controller as well as some of the risks and challenges that had to face and some that the future may pose to the current implementation.

However, some of these challenges have simple solutions as we stated. For instance, the battery level of a smartphone depletes in approximately 12 hours of continuous requests for location updates [OPM12] and this time can be increased with the use of a battery charger connected to the bus itself. Also, the accuracy level of location and time prediction is possible to be acquired if the company provides complete and descriptive data, mainly related to distances and estimated time between bus' stops.

Some of the risks appointed in previous sections may also prove little to nothing. GPS connection may be quite difficult in the countryside but in urban areas it is very effective. Also, nowadays a huge portion of public transportation are equipped with Wi-Fi connection, for the application to transmit data to the server. Finally, the planned interface for SAE Light Controller will be as simple as possible, to minimize possible input errors from the driver; these inputs will be really important to specify which route the bus will traverse, so the trip can be correctly identified for the algorithm to work as it is expected.

Chapter 4

Implementation

SAE Light Controller is a mobile application for Android devices, with Android 4.4 (KitKat) minimum version required, with a client-server architecture. The communication protocol between the client, developed in Java for Android, and the server, developed in Java, is UDP (User Datagram Protocol). This protocol was chosen because it's simple, fast and the possibility to lose some data does not present a problem because the readings and calculations are made with a 5 seconds' timespan and for the TTP calculation, after receiving the data from the server, the application does not require Internet connectivity. Internet connectivity is only needed to identify the route, get some related data from the database, track the bus' positions through time and close the running thread when the trip ends.

When the user of SAE Light Controller starts the application, the driver faces a simple form that he/she must fill with the bus' number, the route's direction and the route's starting time as shown in Figure 4.1.

The driver's inputs in this screen are fundamental for identifying the specific trip and the application to work as expected. Therefore, the bus' number, route's direction and the trip's start time should be written as in the database.

When the "LAUNCH MAP" button is pressed, SAE Light Controller sends a message with this data to the server to get the necessary data, to apply the Kalman filters, relative to that specific route. After this, the server will query the database to get the route that corresponds to the data input and get some information such as the trip's total distance and the expected arrival in the timetable.

With the message sent to the server, the application launches a Google Maps activity, using Google Maps API v2, pinpointing the user's current location with a marker, as shown in the Figure 4.2. For this, we used the Android permission "ACCESS_FINE_LOCATION", that allows the API to determine the most accurate location possible using available location providers like GPS, Wi-Fi and mobile data ¹. The application obtains the vehicle's location to position the vehicle on the map so that the driver can check his/her position on the map.

¹<https://developers.google.com/maps/documentation/android-api/location>

Implementation

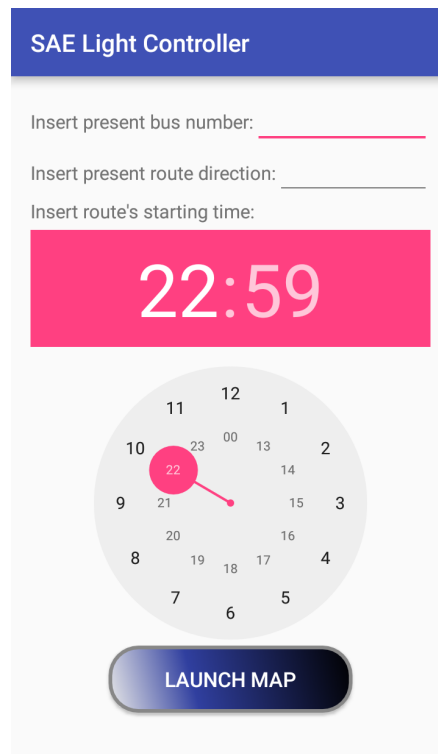


Figure 4.1: SAE Light Controller Main Activity screen

The blue dot is the real-time position of the bus and the marker represents the bus position sent to the server in that specific reading. Sometimes this causes the blue dot and the marker to not occupy the same position on the map because client-server communication is set in 5 seconds timespan, as seen in Figure 4.3.

The blue arrow next to the blue dot points to the direction the bus is travelling. When the bus is stopped, this arrow drifts and points to random directions thanks to position and velocity errors. However, this behaviour does not pose a problem. By empirical observation, we decided to ignore changes when velocity is under 0.1 meters per second (m/s) to avoid states where the velocity is 0 and to ignore the small drift observed when the bus is, in fact, completely stopped.

Meanwhile, the Android device registers the travelled distance, the elapsed time, velocity and measurement accuracy to apply the Kalman filter and get the prediction of the estimated time of arrival. This way the driver can check if the bus is ahead or behind the schedule.

After applying the filters, we get the prediction. This prediction is the amount of time estimated, given the circumstances, to reach the route's last stop. Having this, we can do a simple calculation of the estimated time of arrival and display this in the Maps Activity screen.

Finally, a communication thread is started to send to the server the current latitude, longitude, timestamp, velocity and Google Maps location's measured accuracy and lastly all the Kalman filter's variables. The goal of sending this to the server is to store in the database a history of the trip, both what's important for the driver and what's important for checking how the Kalman filter is working in the given circumstances. This data will be important in the future to send from the

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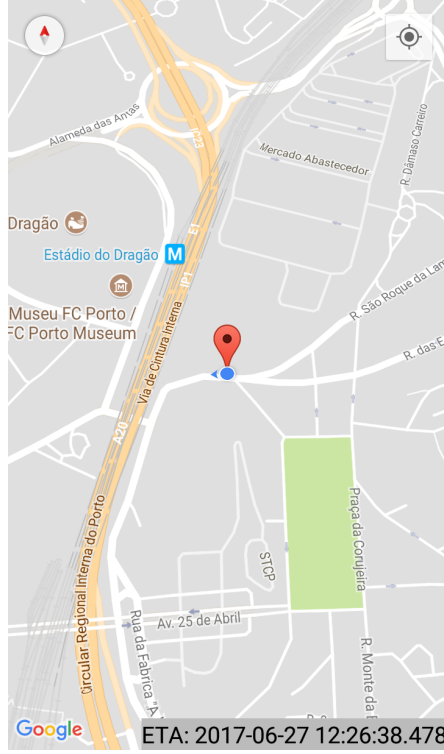


Figure 4.2: SAE Light Controller Google Maps activity screen

server to public transportation customers by some online platform, application, dynamic message signs at bus' stops and so on and to be able to analyse the collected results for this dissertation.

4.1 Kalman filters

As mentioned in the literature review, the Kalman filter is a linear recursive predictive update algorithm and a very reliable implementation solution for calculating the TTP, namely for real-time use. Our algorithm is composed by a constructor, to initialize some variables, and an `apply` method, to calculate the estimated time prediction.

To implement the Kalman filters, the formulas we used for defining the model of our problem are:

- State transition factor: normally it's a constant and for our case defining it as 1 seems to be enough.

$$state_transition_factor = 1$$

- Velocity: current velocity of the bus.

$$velocity = \frac{distance - last_distance}{timespan}$$

Implementation

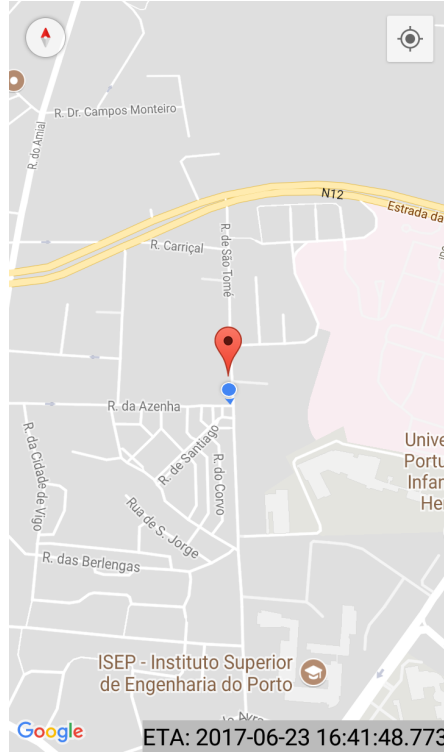


Figure 4.3: SAE Light Controller Google Maps position and last stored position difference

- Velocity error: inaccuracy of the current velocity measure that depends from the position accuracy obtained from Google Maps API.

$$velocity_error = \frac{\sqrt{position_error^2 + last_position_error^2}}{timespan}$$

- Estimated time: we measure the estimated time of arrival by using a simple equation with the remaining travel distance and current velocity.

$$estimated_time = \frac{total_distance - distance}{velocity}$$

- Estimation error: inaccuracy of the current estimated time of arrival.

$$timespan * estimated_time * \sqrt{\frac{estimation_error}{total_distance - distance}^2 + \left(\frac{position_error^2 + last_position_error^2}{distance - last_distance}\right)^2}$$

After defining our model, we must apply the filters in two different steps: predict and update. For the predict step:

- Prediction error: inaccuracy of the travel time prediction.

$$prediction_error = state_transition_factor * last_prediction_error * \\ state_transition_factor = last_prediction_error$$

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- Prediction: travel time prediction; note that the control signal of our model is the elapsed timespan and its factor is -1, therefore the TTP is expected to decrease over time.

$$\begin{aligned} prediction &= state_transition_factor * last_prediction + control_signal_factor * \\ control_signal &= last_prediction - timespan \end{aligned}$$

And for the update step:

- Gain: tradeoff between estimation and prediction.

$$gain = \frac{prediction}{prediction + estimation_error}$$

- Updated prediction: applying the gain, the travel time prediction is updated.

$$updated_prediction = prediction + gain * (estimated_time - prediction)$$

- Prediction error: updates the inaccuracy of the travel time prediction.

$$prediction_error = (1 - gain) * prediction_error$$

Having this knowledge present, it is possible to implement a Kalman filter class for calculating the TTP of a bus' trip. The implemented algorithm follows strictly what is described on `constructor` and `apply` further subsections of this chapter.

4.1.1 Constructor

The Kalman filter class constructor is called in Maps Activity on the `onCreate` method. The constructor's parameters are:

- Total distance: Trip's total distance, measured in meters, through the use of Google Maps. When the driver specifies he desired route, we know the its total distance in meters.
- Prediction error: This value, between 0 and 1, should not be 0 otherwise it will remain 0 forever. This value is updated every 5 seconds' timespan, tending to a fixed value, and it is related to the device. Every time the bus' trip ends, the last value is stored in the device.
- Estimated time: Difference between the end and starting times, in milliseconds, of the specified bus trip.

The constructor initializes the Kalman filter's object with these described values. It also initializes the current travelled distance as 0 meters and the updated prediction variable with the estimated time, because, in the first iteration of the algorithm, the TTP is the scheduled in the bus' timetable. All these values are necessary, as described in this chapter, to run the Kalman filter algorithm.

4.1.2 Apply Kalman filter

The Kalman filter class `apply` method is called in Maps Activity on the `onLocationChanged` method. This method is the one to really initialize the Kalman filter algorithm. The method's parameters are:

- Timespan: difference between the current timestamp and the last measured location's timestamp, that is, the elapsed time between 2 consecutive readings.
- Distance: Length between current location and last measured location.
- Velocity: Current bus' travelling speed, in meters per second.
- Position error: Current Google Maps API v2 location's measured accuracy, in meters.

The `apply` method sums to the current travelled distance with the received distance parameter. Then, this method firstly calls `calculateError`, secondly `predict` and finally `update`, consequently returning the TTP. All these methods will set the variables for each other, so that the `apply` method, before returning, has the TTP, for that iteration, calculated and ready to be displayed on the map for the driver to consult.

4.1.2.1 Calculate Error

The Kalman filter algorithm method `calculateError` is called on the `apply` method. This method's parameters are the same as the `apply` method, besides distance. This new distance parameter is the current travelled distance, updated in the beginning of the `apply` method.

Firstly, it calculates the velocity error, as described earlier in this chapter, and, after this, if the bus' current velocity is under 0.1 meters per second, then the function ends, otherwise it updates the Kalman filter object's estimation error for the current state. The estimation error is calculated as described earlier in this chapter, using timespan, estimated time, position error, last iteration's position error, current travelled distance and last iteration's travelled distance.

4.1.2.2 Predict

The Kalman filter class `predict` method is called on the `apply` method. This method's parameters are timespan and velocity like the `apply` method.

Firstly, this function updates the mobile device's prediction error, as described earlier in this chapter, and, if velocity is below 0.1 meters per second, then the function ends, otherwise it calculates the prediction, also as described earlier.

4.1.2.3 Update

The Kalman filter class `update` method is called on the `apply` method. This method's parameter is velocity like the `apply` method.

If the bus current velocity is below 0.1 meters per second, it defines the Kalman filter's gain as 0, otherwise the function calculates the gain and the estimated time for arrival. Then, the function updates the prediction or, in other words, the TTP, using the calculated gain and estimated time, and finally updates the prediction error value. Note that the calculation of gain, estimated time, travel time prediction and prediction error are earlier described in this chapter.

4.2 Conclusion

The main challenge of this implementation was to define our model, so the problem can be linearised for us to be able to apply a Kalman filter in each state to calculate the TTP. After we defined our model, we are ready to apply the Kalman filter by calling `predict` and `update`. On the predict step we simply update the values of the prediction and its error and, on the update step, we use these values to calculate the gain. The gain is what measures if, in this step, the estimated prediction is relevant. Then, we update the prediction error having the gain in mind: if the gain tends to 0, the prediction error tends to be unchanged.

The prediction error is stored locally on the device because it is influenced by the device's GPS accuracy. By saving this value, knowing that, in the Kalman filter algorithm, the prediction error tends to stabilize, the application is able to start calculating the TTP accurately from the route's start and do not have to wait for it to stabilize every bus' trip.

It is also important to note that, if the bus is stopped the velocity will be equal or approximately 0, thanks to the velocity error, calculated using the position error. If this happens, that is, when the velocity is under 0.1 meters per second, the prediction keeps unchanged and the gain is 0, therefore the estimated prediction prevails, ignoring some position drift.

Implementation

Chapter 5

Test results and analysis

For the implementation and testing phases, the public transportation company STCP (Sociedade de Transportes Coletivos do Porto) provided some data about 3 different bus routes: 301, 401 and 806. Route 301 is a bus with a circular trajectory around the city and both 401 and 806 routes are buses with 2 different direction trajectories. Unfortunately, because the provided data did not include weekend routes, we did not have the time needed to test route 806 or to collect more data from the other routes.

With this provided data and at the time of testing, we did real-time field testing for only routes 301 and 401. One of the directions of route 401 was modified thanks to some street construction works, therefore it is impossible to analyse the results for that specific trip in the temporarily modified direction and, for data consistency, we collected data for 2 runs of route 301.

The Android device we used for collecting data was a Xiaomi Redmi 3s that we used for our bus runs.

5.1 Collected results

In Figures 5.1, for route 301, and 5.2, for route 401, we can observe the maps according to the readings made. These maps were built by collecting position data from the application and they show where the accuracy dropped, mainly when the bus makes a turn. Sometimes position readings seem missing but that's because, with higher speeds, the 5 seconds' timespan does not allow for a complete drawing of the route.

First of all, the collected data of route 401, direction "Volta", was discarded given that there were works on the road and, consequently, the route was temporarily changed, differing from the scheduling we obtain from STCP.

In the Figures 5.3 and 5.5, for route 301, and Figure 5.7, for route 401, we relate the estimation error with position standard deviation and current velocity over time. In these graphs, we use a logarithmic scale in the errors' axis because some registered values proved to be difficult to visualize a relation between all the variables if we used linear scale. This way, only the big variations will be visible.

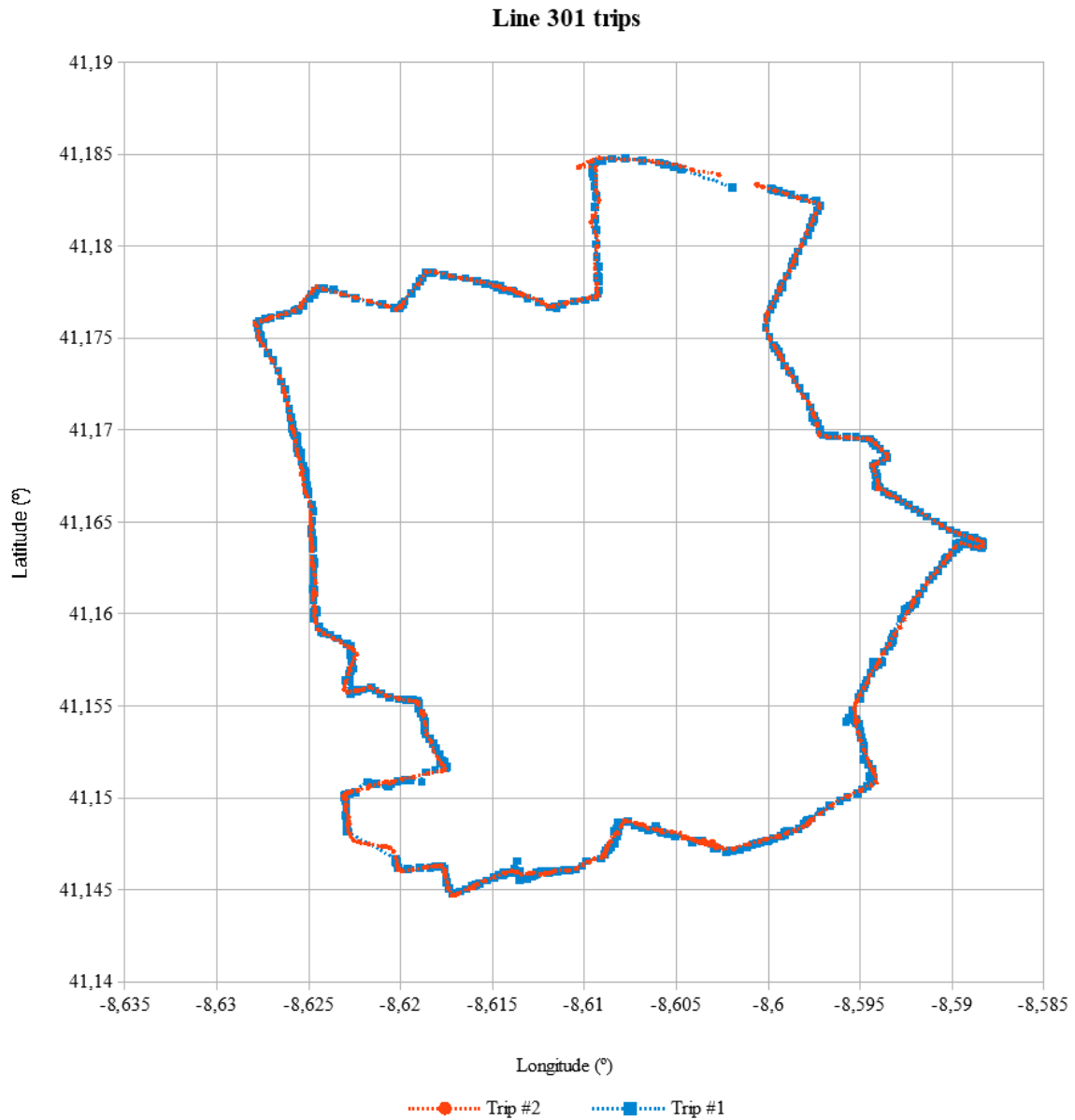


Figure 5.1: Route 301 positions recorded for two different bus trips

Finally, in the Figures 5.4 and 5.6, for route 301, and Figure 5.8, for route 401, we relate the scheduled time of arrival, the calculated estimated time of arrival (ETA) and the actual time of arrival with position standard deviation over time.

5.2 Results' analysis

On the routes we observed, the total distance travelled is greater than the one estimated by using Google Maps. This can be related to GPS drift and/or a bad calculated trip's total distance. The first possibility could be measured if we had more than one different device, mainly one with a

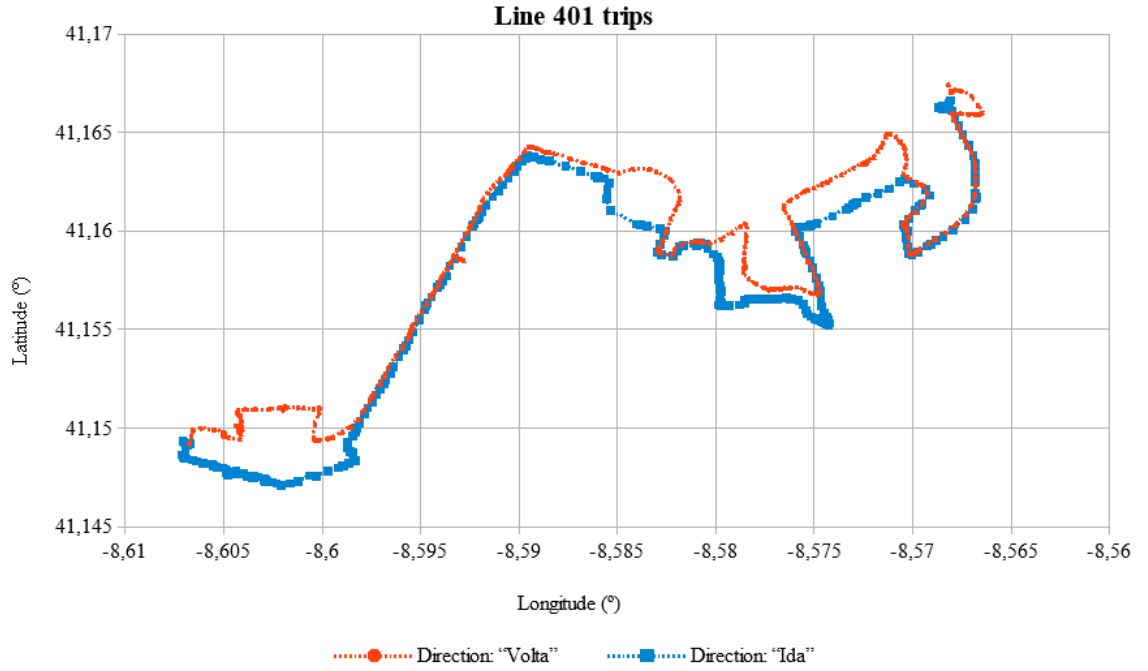


Figure 5.2: Route 401 positions recorded for two different bus trips, with different directions

good GPS signal and the other with a weaker one and the drift could be softened by setting the bus current position to the nearest position belonging to the route. The second one could be enhanced, as written in the Future Work chapter, if the public transportation's company had themselves the total distances of all bus routes, or even better, all the distances between all the bus stops.

On the first trip of route 301 the results have an expected behaviour. The TTP tends to the arrival time line and almost intercepts it. On the second bus trip, and also on route 401, the algorithm, in the end, seems to start having the expectable behaviour, but proves to be far from reality. Mainly for the second trip on route 301, as seen in Figure 5.6, the huge values of the position standard deviation seems to not affect the prediction. As observed, the bus being behind or ahead schedule could be related to the calculated TTP. We were not able to identify this possibility because bus routes have a fixed total distance, therefore we could not analyse more iterations of the algorithm and, due to lack of time, we could not collect more data by doing more bus trips.

Instead of using the last prediction error to save locally, the average of the prediction error during the bus trip should be used. Thus, we are able to avoid situations where the last reading had a large standard deviation position, thus making the prediction error reach very high values, and write an inconsistent last value of this error.

As observed in the Figure 5.9, the prediction error rises when the time prediction tends to 0, that is, when the bus trip nears its end. By saving locally the average prediction error from the last bus trip, the prediction error will tend to decrease when the route starts and then increase as the TTP decreases. This behaviour is expectable the way prediction errors are updated, as it was described in chapter 4 of this dissertation.

Test results and analysis

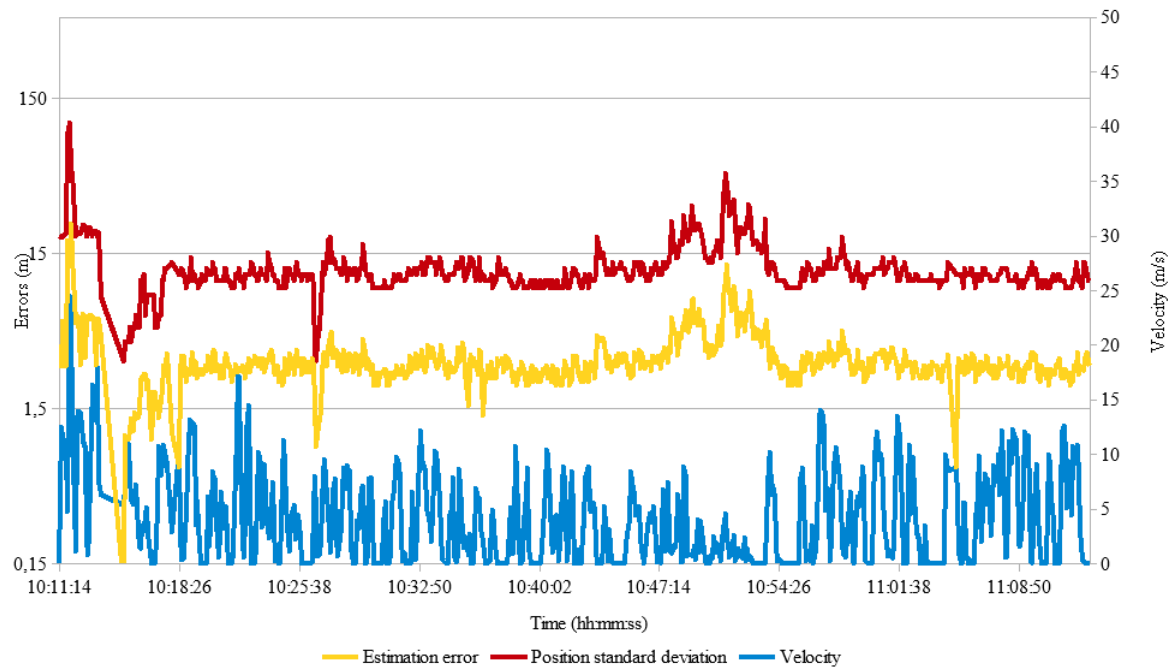


Figure 5.3: Estimation errors for the first trip of route 301

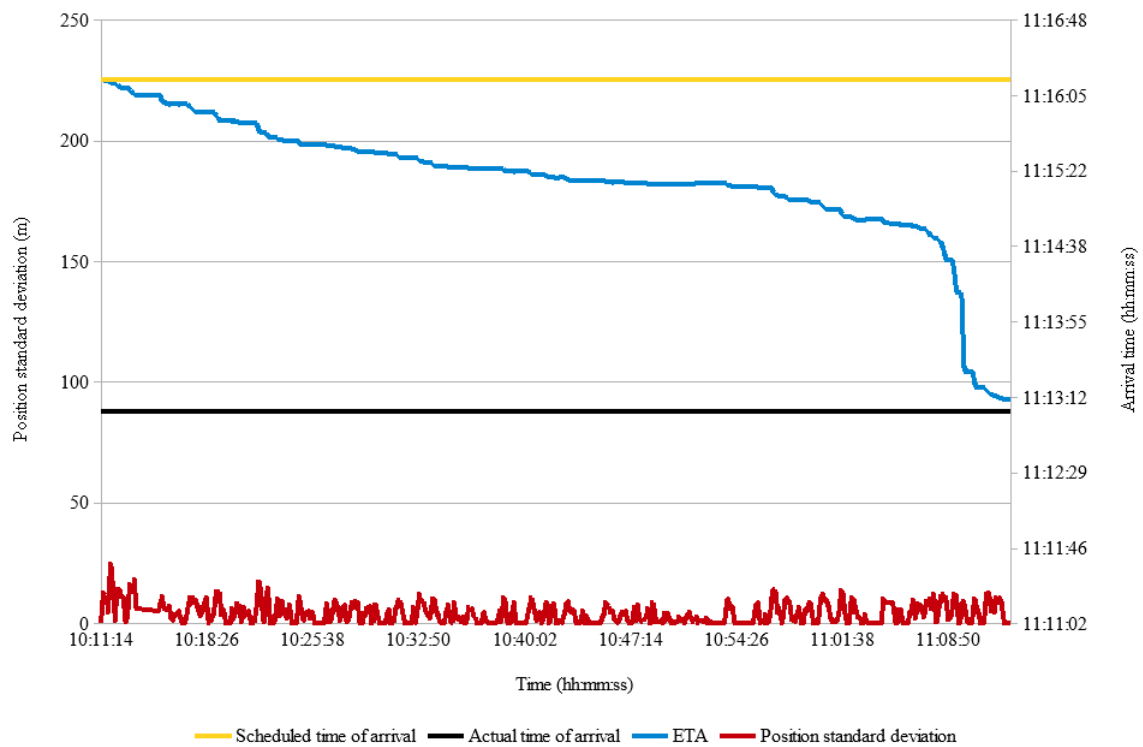


Figure 5.4: Comparison of arrival times for the first trip of route 301

Test results and analysis

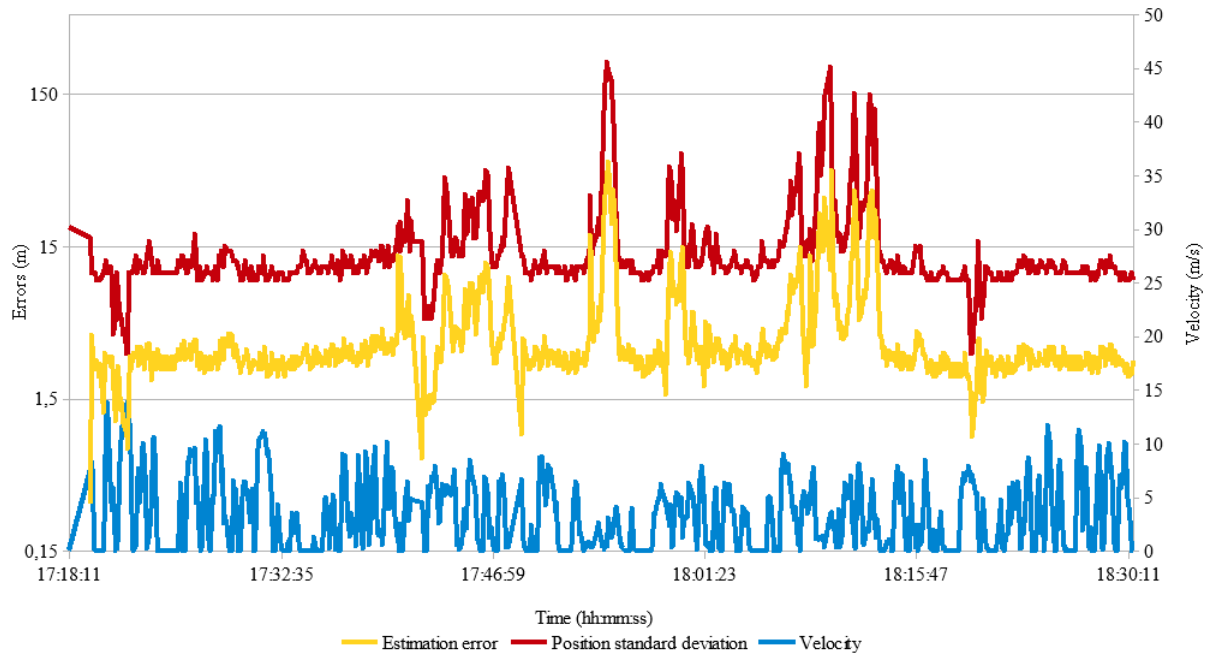


Figure 5.5: Estimation errors for the second trip of route 301

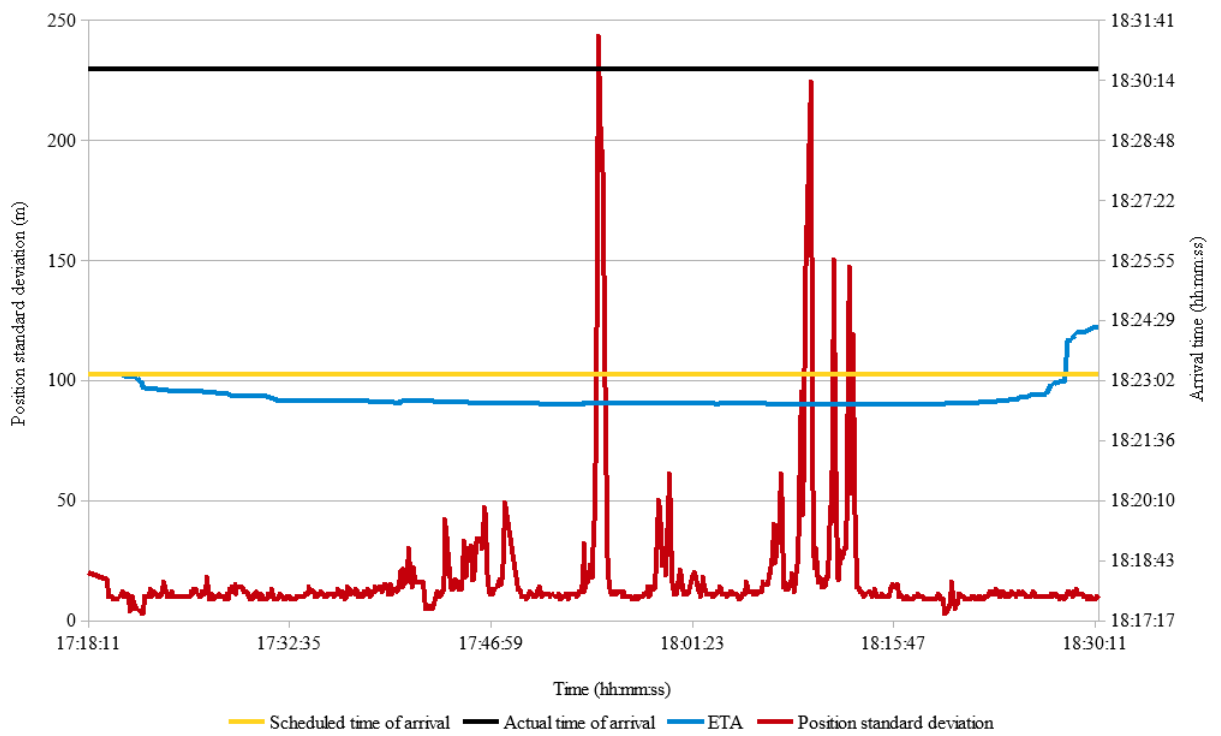


Figure 5.6: Comparison of arrival times for the second trip of route 301

Test results and analysis

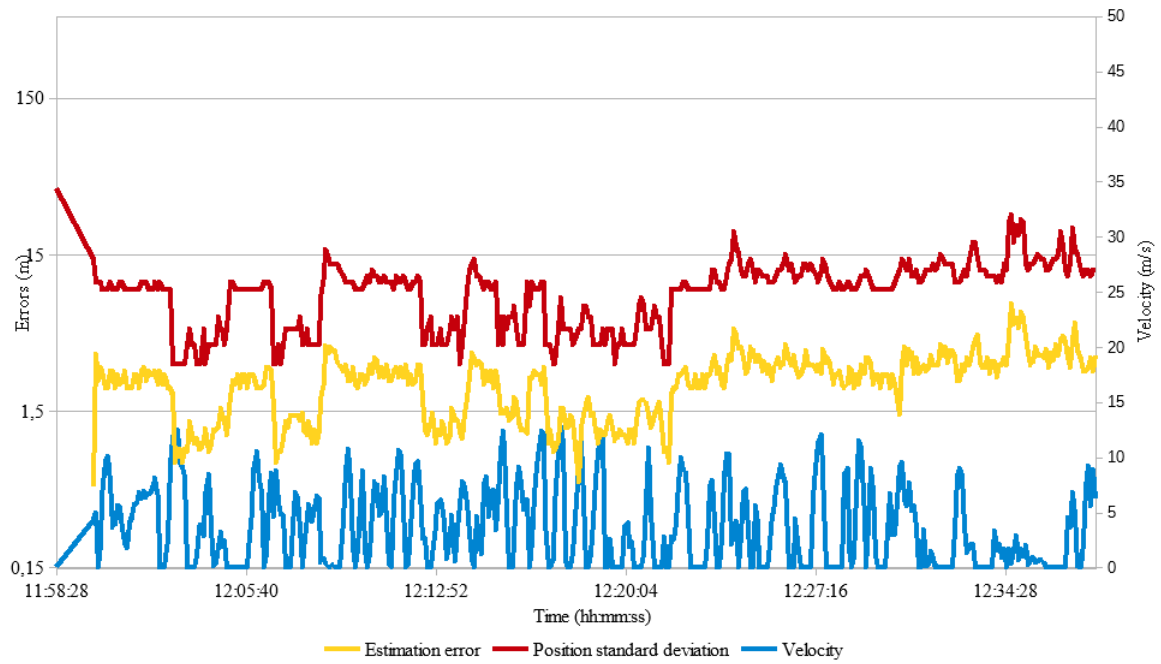


Figure 5.7: Estimation errors of route 401

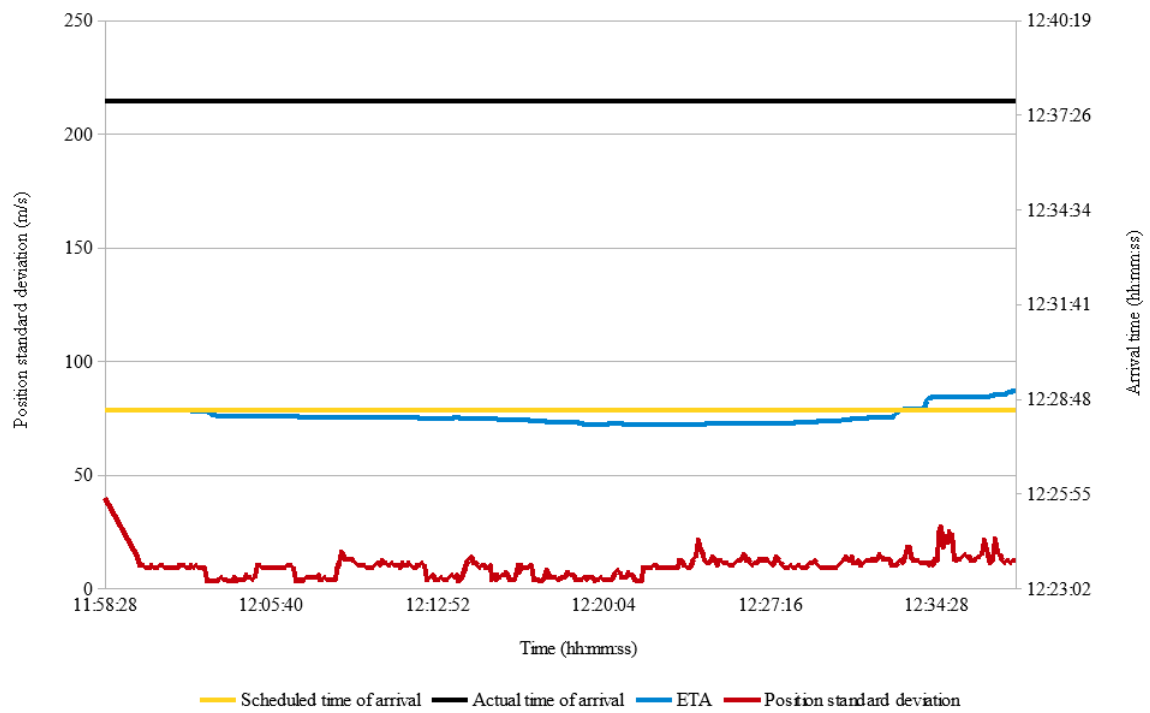


Figure 5.8: Comparison of arrival times of route 401

Test results and analysis

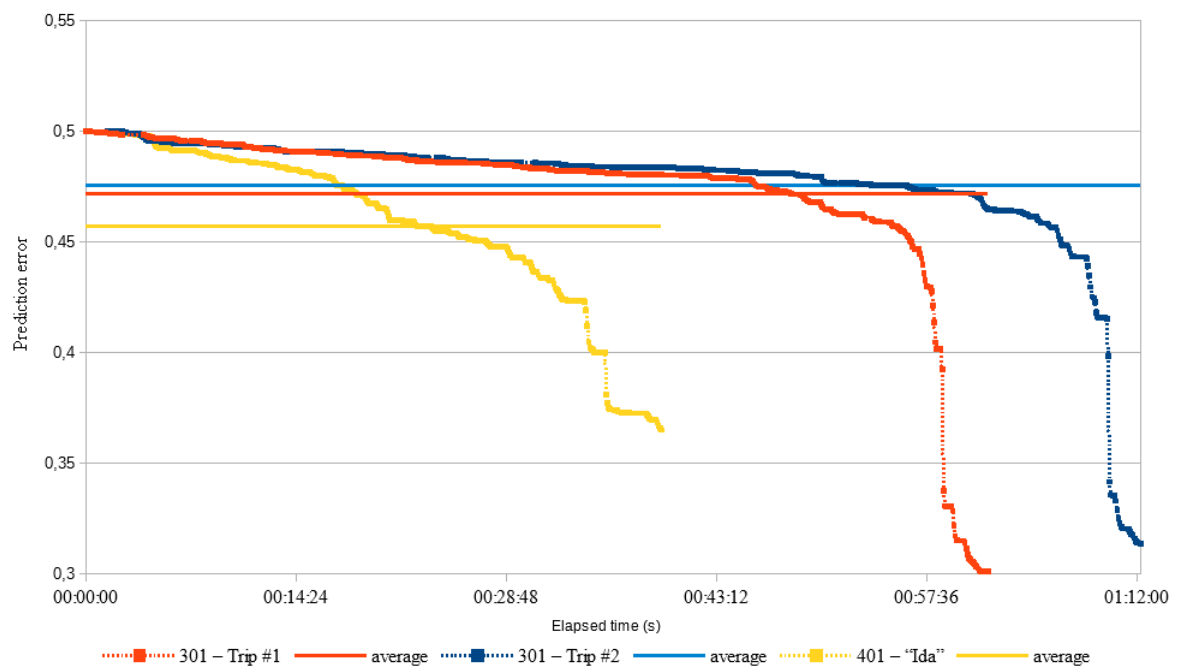


Figure 5.9: Prediction errors of carried out bus trips

Test results and analysis

Chapter 6

Conclusion and Future Work

Conclusion

Nowadays the AVL systems used on the market are too expensive so that small and medium companies can easily acquire these equipments. These systems have several functionalities that are useful to the bus driver, whether they are tracking, farebox, travel time prediction or others.

While some features are relatively easy to implement, the most challenging in terms of complexity is the TTP calculation. According to the literature review, we could observe that the use of Kalman filters is highly recommended and currently used in the calculation of TTP in real time.

Through the data recorded, the SAE Light Controller proved that an Android device is able to calculate the TTP, in real time, using the algorithm developed through the use of Kalman filters. Although some results fail to confirm this success, we will present some possible future work so that the accuracy of the algorithm increases to something competitive with the actual AVL systems used on the market.

SAE Light Controller also proved to be able to overcome the two biggest challenges that it had besides the calculation of the TTP: the Internet connection and the use of the battery. The application only requires Internet connection to launch Maps Activity with the necessary information to the algorithm, to record in the database all the readings made for the tracking of position, time, start and end of route. Regarding the use of the battery of the device, it has an expected consumption, and is perfectly controllable through the use of a cigarette lighter charger.

In conclusion, an Android device can be used as a way to compete with current AVL systems, thus reducing the cost of acquiring the equipment in a very considerable amount, and there are still other possible variables to be added, such as future work, to increase the accuracy of the TTP calculation or the addition of more functionalities, in order to completely emulate a current AVL system.

Future Work

SAE Light Controller is capable of competing with current AVL systems on the market in calculating the travel time prediction, one of the most challenging aspects of these systems. However, it would be interesting to minimize positioning errors by assuming that the bus is always in the nearest point of the route's polyline and, therefore, minimize the current travelled distance, ending in a better travel time prediction calculated with the algorithm. To achieve this, the public transportation's company must be able to define a polyline for each route comprised of a set of location points.

For an even better calculation of the TTP, instead of only working with the start and ending times for defining the trip's estimated time, define a trip as a set of smaller trips with start and ending times between each stop. Therefore, the application will be able to calculate the TTP between each and every stop in the bus route. This way, the time prediction of bus' arrival is even more accurate.

Google Maps has also a traffic control API and, with this, once the driver starts the bus trip, he/she would have a prediction already taking into account possible traffic delays between bus stops. This way, the calculated prediction would not only be influenced by real-time conditions, but also start taking account the route's traffic conditions.

The use of more different sensors, such as the accelerometer of the device among other possible, increases the complexity of the algorithm and, consequently, increases the precision of the data, minimizing the accumulated error.

In the testing phase, it may be interesting to try out different data reading frequencies. In this way it is possible to verify if the increase or reduction of this frequency causes more precise results and what is its impact in the time of processing and use of the battery.

Finally, by storing the bus' location in the database, SAE Light Controller is able to achieve many interesting features, currently associated with fully developed AVL systems, such as:

- Bus tracking: By sending the stored coordinates to every application, the bus' driver will be able to plan if he wants to stop and increase the delay in an already behind the schedule trip or let the customers on the bus' stop to wait for the next bus. The companies will also be able to track the bus to be able to better plan its schedule efficiency, better respond to an emergency, etc.
- Customer assistance: Let the customers know, in real-time, the current time needed for the bus to arrive, through the use of several methods, such as dynamic message signs;
- Manager of headsign and farebox;
- Onboard automatic passenger counting: let the companies to record the number of passengers boarding.

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